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Assessment of the Requirements of Smart production Systems in SMEs: Intuitionistic Fuzzy Best-Worst Method and Total Interpretive Structural Modeling Integrated Method

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Abstract
Today, manufacturing companies must address the increasing trend of smart manufacturing (SM) to maintain their competitiveness. Concurrently, small and medium enterprises (SMEs), which constitute the backbone of numerous production economies, are endeavoring to comprehend the complexities associated with implementing this advanced production system. However, many of these enterprises are hesitant to adopt SM due to insufficient human and financial resources. The transformation of a company's existing system into smart production systems, as opposed to implementing smart manufacturing from the outset, necessitates greater financial and temporal investment. Consequently, it is imperative to consider and integrate effective requirements for smart production systems during the design phase. This study aims to identify these requirements, ascertain their significance, and comprehend the contextual relationships among them. To achieve this, a systematic review method is employed to identify the requirements, followed by the Intuitionistic Fuzzy Multiplicative Best-Worst Method (IFMBWM) to determine their weights. Finally, the TISM method is utilized to understand the interrelationships and compare the levels obtained with the results of the best-worst method. The results indicated that the effective requirements can be categorized into eight main criteria. The highest and most fundamental criterion is the requirement for digitalization and real-time data connection. The second criterion is automation, followed by smart communication with beneficiaries as the third. Overall, small and medium-sized enterprises should prioritize information technology and artificial intelligence requirements to advance towards smart production systems.
Keywords: *Smart Manufacturing Systems, Small and Medium-Sized Companies, Intuitionistic Fuzzy Multiplicative Best-Worst Method, Total Interpretative Structural Modeling*

Introduction

The recent advancements in smart production have significantly propelled the industry forward. The successful future of manufacturing hinges on the adoption of smart manufacturing practices. The development of technology, along with the recording and analysis of data in production sectors, enhances productivity, efficiency, process capability, and business sustainability. Manufacturers that fail to adopt smart manufacturing may struggle to compete in the global market and risk becoming obsolete over time (Bello et al., 2024).

In recent years, the industrial environment has undergone significant transformations with the advent of new theoretical models and technologies associated with the fourth industrial revolution, also known as Industry 4.0 (Kagerman et al., 2013; Sandler, 2013; Rauch and Vickery., 2020). Industry 4.0 represents the fourth phase of industrial evolution, driven by smart manufacturing

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(Rauch and Vickery., 2020). Within this revolution, the smart factory is regarded as the ultimate stage of Industry 4.0. Manufacturing companies are striving for advancements in this domain by integrating various advanced technologies to maintain their competitiveness (Jung et al., 2021). Consequently, Industry 4.0 represents a paradigm shift in production systems, emphasizing the creation of value through smart products, procedures, and processes, with the establishment of smart factories being one of its key features (Simetinger and Basl, 2022). Generally, smart manufacturing is a contemporary manufacturing model where machines are fully networked, monitored by sensors, and overseen by computational intelligence designed to enhance system productivity, product quality, and sustainability while reducing costs. The recent advancements in IoT, artificial intelligence, and related technologies provide essential enabling solutions to advance modern manufacturing (Haricha et al., 2023). As a result, smart manufacturing leverages Industry 4.0 technologies to enhance the efficiency, productivity, and flexibility of production systems, processes, and services. Industry 4.0 and smart manufacturing offer several advantages, including improved production efficiency, cost reduction, enhanced product quality, and increased agility in responding to market changes. These benefits provide significant potential for manufacturers to optimize their operations, reduce costs, and remain competitive (Mourtzis, 2024).

On the other hand, SMEs have been recognized as the main sources of employment in developed and developing countries in recent years. These companies play an important role in creating new jobs, innovation, flexibility and economic growth. According to Drucker, to remain competitive in the face of changes in the political, social and economic environment, new; requires innovative strategies. Small and medium-sized enterprises are trying to actualize the principles of Industry 4.0 by implementing specific measures to use its potential and increase their productivity. Meanwhile, companies, particularly SMEs, are endeavoring to actualize the principles of Industry 4.0 by implementing specific measures to harness its potential and enhance their productivity (Rezaei et al., 2021). Meanwhile, companies, particularly SMEs, are endeavoring to actualize the principles of Industry 4.0 by implementing specific measures to harness its potential and enhance their productivity (Matt et al., 2014). However, they often face challenges in understanding how to approach Industry 4.0 or initiate the introduction and implementation of its concepts. According to a survey, many SMEs struggle with increasing product variety and personalization. Price competition, stringent quality requirements, and short delivery times are becoming increasingly significant. Due to their flexibility, entrepreneurial spirit, and smart production capabilities, SMEs have demonstrated greater resilience compared to large and multinational companies (Rauch and Vickery, 2020).

The technologies associated with smart production systems contribute to achieving reliable, flexible, and stable processes. Companies that utilize or plan to transition to smart production systems should consider the features that enable these systems to efficiently perform production processes. These features, which facilitate smart production systems, will also be beneficial for the development of the technologies employed (Kılıç and Erkayman, 2023). The requirements of smart manufacturing systems have evolved into a complex field of requirement engineering, encompassing not only technical aspects but also the realization of multifaceted sustainable value. The list of requirements for smart manufacturing systems includes fundamental sustainable value streams among related stakeholders, key stakeholders, and achievement pathways for smart manufacturing systems. However, systematic analyses of these requirements remain relatively scarce (Qu et al., 2023). Conversely, classifying, examining relationships, and determining the importance of each requirement or facilitating feature will assist companies adopting smart production in developing strategies to mitigate production issues. Therefore, soft computing approaches with flexible computing capabilities offer a unique method for organizations transitioning to smart manufacturing systems to identify critical capabilities and optimal technologies (Kılıç and Erkayman, 2023).

According to the research literature, several studies have addressed the requirements necessary for establishing a smart factory. However, there is a paucity of studies focusing on the importance of these requirements and the analysis of their internal relationships within SMEs. This research employs a multi-method approach to address the following questions:

What requirements are effective in creating and utilizing smart production systems in SMEs?

What are the relationships and influences among these requirements, and how important is their application for smart production systems?

The IFMBWM is applied to determine the relative importance of these requirements within the selected context. One of the key features of the Best-Worst Method is its ability to achieve more consistent pairwise comparisons and produce more reliable results. Subsequently, the TISM method was employed to understand the contextual relationships among these requirements and to compare the obtained levels with the results of IFMBWM. Previous research confirms that TISM is a highly effective multi-criteria decision-making tool that aids in theory development. This technique not only identifies relationships between variables and creates a hierarchical framework but also includes qualitative evaluation of these links to uncover their underlying causes (Dubey et al., 2018). Additionally, this technique has been utilized to investigate the contextual relationships among the effective requirements for the creation and application of smart production systems in small and medium-sized enterprises.

Literature Review

Numerous studies have been conducted on the literature of smart production systems, their features, and the technologies employed, and research in this area is ongoing.

Kumar (2018) reviewed the technologies critical for enabling smart manufacturing, including augmented reality and virtual reality (AR & VR), the Internet of Things (IoT), human-robot interaction, and cyber-physical systems (CPS). His study also examines the challenges that need to be addressed, such as existing methods and material technologies. Lu and Weng, (2018) conducted a literature review to identify 19 technologies for smart manufacturing industries in Taiwan that significantly impact the development of smart manufacturing both today and in the future. They proposed market maturity estimation with smart manufacturing technology. Mittal et al., (2019) reviewed the existing knowledge related to smart manufacturing and organized various features, technologies, and enabling factors. Qiu et al., (2019) proposed an integrated method for assessing the requirements of smart manufacturing systems in the era of Industry 4.0 and the Internet of Industrial Things. This method employs systematic research to identify, classify, and evaluate the requirements of smart production systems, considering uncertainty, multiple users, and multiple disciplines. The results of this research provide a preferred method for considering and framing the requirements of smart production systems. Kusiak, (2019) explained that the main features of smart production systems are based on data, network connectivity, resource sharing, durability, and sustainability. They focused on manufacturing flexibility and sustainability, as these areas had received only limited attention in the literature.

Mittal et al., (2019a) conducted a systematic review to identify the fundamental principles and existing methods for adopting smart manufacturing. They found that smart products, parts and materials, interoperability, data sharing systems, and standards are widely recognized as essential principles for manufacturers. Mahmoud et al., (2020) proposed a four-step method to assist stakeholders in creating a smart manufacturing system with enhanced capabilities while increasing manufacturers' awareness of Industry 4.0 adoption. These four stages include the configuration of systems and robots, smart system components, smart system integration, and evaluation and selection. Ghobakhloo's, (2020) study demonstrated a complex priority relationship between smart production and the factors influencing digital technology acceptance. This study, through an advanced survey, content analysis of the research literature, consultations with university and industry experts, and the implementation of interpretive structural modeling methodology, identified eleven enabling factors and examined the contextual relationships among them. This study further elucidated the intricate precedence relationships among the determinants of IDT adoption in smart manufacturing. Phuyal and Bista, (2020) redefined smart manufacturing systems, assessed the current state of the program, and analyzed the gap between the present and the anticipated future of manufacturing systems with the aid of smart manufacturing technology. Larsen and Lassen, (2020) reviewed the considerations necessary when designing innovation processes for smart manufacturing. It is crucial to identify the parameters that influence the outcome of innovation during the design phase. Rauch and Vickery, (2020) compiled a list of requirements and needs for designing a smart manufacturing system in small and medium-sized enterprises. In another study, Sharma and Villányi, (2023) employed an analytical and descriptive research method to identify and evaluate functional and non-functional, technological, economic, and social evaluation components essential for assessing smart production systems. They presented a predictive analysis framework, which serves as a key component of many decision support systems, to assess company needs and propose and prioritize smart manufacturing system services. According to this study, analyzing the importance of services and operations of smart manufacturing systems aids traditional manufacturing organizations in achieving automation and advanced technologies through smart data analysis and real-time data connectivity.

Malaga and Vinodh., (2023) identified factors influencing the acceptance of smart and sustainable production systems and ranked the most effective factors using the fuzzy TOPSIS multi-criteria decision-making method. According to their analysis, this approach assists industry practitioners in selecting the most effective factors to successfully adopt smart and sustainable production systems and compete globally. Qu et al., (2023) presented a systematic method for compiling the list of requirements for smart manufacturing systems and elucidating the complex relationships among multi-stakeholder smart manufacturing systems. This research introduced a comprehensive approach to capture these requirements based on the stakeholder salience model and the stakeholder value network. In the second step, a quantitative analysis was proposed to determine the urgency and importance of the requirements using a comprehensive fuzzy Kano model. Finally, the list of requirements was obtained through systematic evaluation methods, including graph theory, dependency matrix, and network statistics. A case study in a Chinese company was also conducted to investigate the feasibility of the proposed approach. In Iran, Ardehi et al., (2023) conducted a study with the aim of designing a model for implementing the fourth generation industry to achieve sustainable development goals in Iran Khodro Company. In this study, interpretive structural modeling (ISM) with MICMAC software was used in the qualitative part to draw the initial model, and in the quantitative part, one-sample t-test and SPSS software were used to assess the current situation. The research findings showed that the collection and analysis of big data affects simulation and automated robots. These factors affect horizontal and vertical integration systems, and as a result, lead to the Industrial Internet of Things, augmented reality, and cybersecurity. In addition, through the cloud computing system, additive manufacturing is affected, and this additive manufacturing leads to sustainable development. As previously mentioned, numerous studies have been conducted on the requirements of smart production systems, with the most significant ones discussed herein. It is noteworthy that, in the majority of the reviewed studies, with few exceptions, these requirements or indicators were merely examined, and the analysis of their contextual relationships was not observed. According to the review of the articles, in some instances, only the prioritization of the requirements or indicators was addressed. Furthermore, most of the studies were not specifically focused on SMEs; rather, they were conducted generally for all companies. Consequently, it can be stated that the solutions proposed by these studies, due to the unique constraints of SMEs, are generally inadequate in addressing their specific challenges.

Materials and Methods

This study has adopted a multi-method approach to address the questions posed in the introduction. As illustrated in Figure (1), the focus group technique was employed for the second research question, utilizing the expertise of subject matter experts in the chosen field. The focus group comprises five academic experts from Shiraz University, specializing in Industry 4.0, production systems, and smart production. Prior to this, a literature review was conducted to extract scientific articles from various databases such as Scopus and Google Scholar, forming the theoretical foundation of the smart production concept. From this stage, 8 requirements and 55 indices effective in smart production were identified. This research investigates eight main requirements.

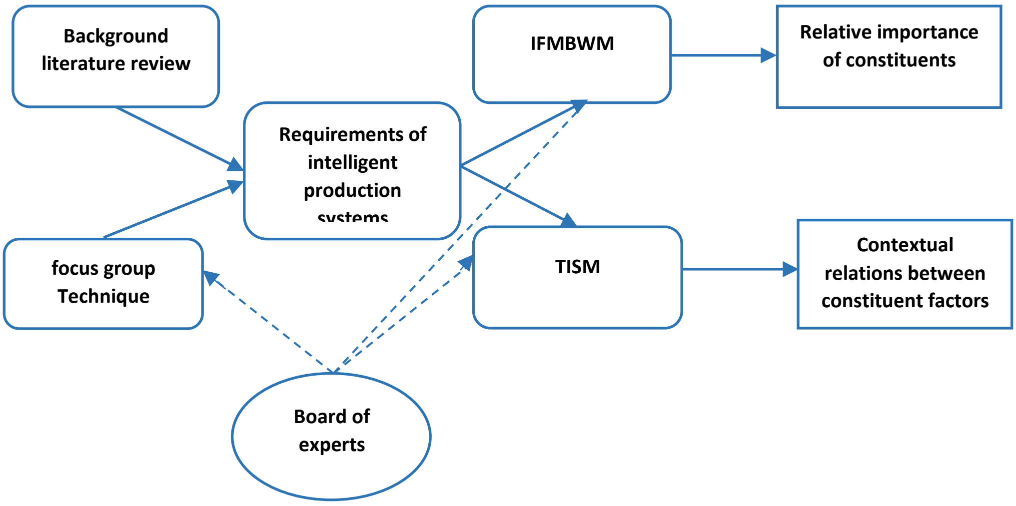

Figure 1. *Research flow chart*

IFMBWM

After the final list of constituent factors was confirmed, IFMBWM was used to find the relative importance of these dimensions in order to formulate their implicit weights and ranks. Rezaei, (2015) introduced the BWM to obtain the weighted coefficients of the criteria using the optimization model. This method uses the approach of paired comparisons to collect the preferences of decision makers. This method has advantages over other methods. Achieving more consistent pairwise comparisons and more reliable results is one of its features. (Rezaei, 2015; Bonab et al., 2023). However, the BWM is inappropriate under uncertain conditions, which further limits the limited applicability of this method.

To overcome this limitation; Mou et al., (2016) proposed a new algorithm to rank criteria and obtain a directed graph. The IFMBWM is a method that has been extended to improve uncertainty conditions. In this method, in addition to the degree of membership, the degree of non-membership is also considered. Therefore, using the IFMBWM makes it easier to respond to environmental uncertainty. It is important to note that the IFMBWM is graph-based, and the data collection method employed is hierarchical analysis, which involves a complete pairwise comparison matrix. The steps of IFMBWM are as follows (Moet al., 2016):

Step 1. Determining the set of decision criteria: determine the set of decision criteria $C = \{c_1 . c_1 . \dots . c_j . \dots . c_n\}$ and based on Intuitionistic fuzzy multiplicative preference relations (IFMPR); Provide $A^{(k)} = (\rho_{ij} . \sigma_{ij})_{n \times n}$, $k \in S . i \in N . j \in N$.

Step 2. Intuitive fuzzy graph-based preference relationships $A^{(k)} (k = 1.2. \dots . s)$ presented by decision makers as weighted geometric aggregation based on intuitionistic fuzzy multiplicative weighted geometric aggregation (IFMWGA) using Summarize from E.q (1):

$$\mathrm{IMWGA}_{\lambda} = \left(\left(\prod_{k=1}^{s} \left(\rho_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{s} \left(\sigma_{ij}^{(k)}\right)^{\lambda_k} \right) \right)_{n \times n}$$

(equation 1[2])

By combining the opinions of experts, the cumulative matrix A (E.q (2)) is obtained as follows. This matrix is similar to the matrix of pairwise comparisons in the hierarchical analysis method.

$$A = \begin{bmatrix} (\rho_{11},\sigma_{11}) & (\rho_{12},\sigma_{12}) & \cdots & (\rho_{1n},\sigma_{1n}) \\ (\rho_{21},\sigma_{21}) & (\rho_{22},\sigma_{22}) & \cdots & (\rho_{2n},\sigma_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (\rho_{n1},\sigma_{n1}) & (\rho_{n2},\sigma_{n2}) & \cdots & (\rho_{nn},\sigma_{nn}) \end{bmatrix}$$

(equation 2)

Step 3. Determining the most important and least important indicators: In this step, the most important and least important indicators should be determined by the decision matrix and the oriented graph. The most important index is indicated by C_B and the worst index by C_W.

In order to achieve this, first, the initial directed diagram is drawn using the information of the consolidated matrix, and then, according to the values of $\rho_{ij} \geq 1$, the final directed diagram is drawn.

Step 4. Determining the optimal weight: After obtaining the directed graph, the optimal weight vectors of the degree of membership and non-membership are modeled using the following relations.

Build models 1 and 2 and get the optimal weights by solving the two models. The optimal solutions of models 1 and 2 are respectively $\xi^* . (\upsilon_1^* . \upsilon_2^* . \dots . \upsilon_n^*)^T$ and $\zeta^* . (\tau_1^* . \tau_2^* . \dots . \tau_n^*)^T$.

Therefore, the optimal weight vector is obtained as: $W^* = \left((\tau_1^* . \upsilon_1^*) . (\tau_2^* . \upsilon_2^*) . \dots . (\tau_n^* . \upsilon_n^*) \right)^T$:

Model 1- Degree of membership:	Model 2- degree of non-membership:
$\min \xi$	$\min \zeta$
s.t. $\left| {}^{\tau_B}/_{\tau_j} - \rho_{B.j} \right| \leq \xi$	s.t. $\left| {}^{\upsilon_B}/_{\upsilon_j} - \sigma_{B.j} \right| \leq \zeta$
$\left| {}^{\tau_j}/_{\tau_W} - \rho_{jW} \right| \leq \xi$	$\left| {}^{\upsilon_j}/_{\upsilon_W} - \sigma_{jW} \right| \leq \zeta$
$\sum_{j=1}^{n} \tau_j = 1$	$\sum_{j=1}^{n} \upsilon_j = 1$
$\tau_1 \geq \tau_2 \geq \cdots \geq \tau_n$	$\upsilon_1 \geq \upsilon_2 \geq \cdots \geq \upsilon_n$
$\xi \geq 0 . \tau_j \geq 0 . \ for\ all\ j \in N$	$\zeta \geq 0 . \upsilon_j \geq 0 . \ for\ all\ j \in N$

Step 5. Obtain the compatibility ratio using equation (1) based on CI1 and CI2 presented in Table 1 as well as the optimal values (ζ^* and ξ^*) obtained in the models.

[2] In this regard, λ_k represents the weight of different experts.

$$Compatibility\ ratio = max\left\{\frac{\xi^*}{CI_1}.\frac{\zeta^*}{CI_2}\right\}$$
(equation 3)

Table 1
Incompatibility index

ρ_{BW}	1	2	3	4	5	6	7	8	9
$CI_1(max\,\delta)$	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23
σ_{BW}	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1
$CI_2(max\,\varepsilon)$	0.08	0.08	0.09	0.10	0.11	0.12	0.12	0.12	0.00

TISM and MICMAC

After reaching the weights that show the relative importance of these factors, TISM technique has been used to understand the relationship between these dimensions and compare the obtained levels with the results of the IFMBWM. TISM is an improvement over ISM; A process that is used to convert unclear and vague mental models into hierarchical structures by interpreting contextual relationships on the interfaces in the diagram for greater clarity. In this study, this technique has been used for structural prioritization of factors to compare with the results obtained from IFMBWM and to discover contextual relationships to answer the second question. The step-by-step process of TISM is as follows: (Sushil, 2012; Sharma et al., 2021).

Step 1. The list of smart manufacturing requirements obtained utilizing the literature review and expert opinions.

Step 2: A pairwise analysis of the relationship between these factors is conducted to create a knowledge base that covers even the transitory relationship with the contextual meaning. (Table 5).

Step 3: Develop the reachability matrix based on the relationships covered by the knowledge base. (Table 6)

Step 4: Step-by-step partitioning to assign levels to factors based on interpretation logic.

Step 5: Developing TISM diagram according to the assigned levels from step 4 and add interpretative logic on the interfaces in the diagram (Figure 2). The binary reachability matrix developed in the TISM process can be used to analyze these factors using MICMAC. This helps to categorize the list of factors into four quadrants including: independent, linkage, dependent and autonomous. The position of these factors is determined by the driving power and dependence of a specific factor in the chosen field of study.

Results

Through a systematic review of the research literature and consultations with experts, the requirements effective in establishing and utilizing smart production systems in small and medium-sized enterprises were identified. These requirements are presented in Table 2.

Table 2
Requirements of Smart production systems

No	Requirements	Salient features
R_1	Modularity	Machine tools and modular material handling equipment as well as reconfigurable devices.
R_2	Agility	Easy to use and change production systems, rapid prototyping technologies and a high degree of adaptability, flexibility and changeability. In order to respond to short-term changes in product volume or type, production systems must be adaptable, flexible and changeable. This allows for a profitable mass customization strategy and enables efficiency.
R_3	flexibility	Flexible workstations, personnel and production processes.

No	Requirements	Salient features
R_4	Digitization and connection of real-time data	Automation, product improvement and management, feedback system and infrastructure, design, supply chain monitoring and control digitally.
R_5	Robotization	Robots under artificial intelligence, cobots and small-scale production, robotic packaging and shipping, robotic and Smart logistics distribution
R_6	Smartening communication with stakeholders	Chatbots, voice of the customer solutions, internal knowledge management and employee development
R_7	Automation	Automatic loading and processing, flow and control of materials between workstations, reinforcement learning tools, as well as automated guided vehicles
R_8	Smartening maintenance and inspection	Online maintenance, remote monitoring and customer troubleshooting, automatic maintenance, augmented reality in services, after-sales maintenance

Source: (Rauch et al., 2019; Rauch and Vickery, 2020; Sharma and Villányi, 2022; Kanakana-Katumba et al., 2022; Sahoo & Lo, 2022; Hammad et al., 2023; Haricha et al., 2023; Kılıç & Erkayman, 2023).

Also, by using the IFMBWM as a decision-making technique, the weight of each requirement was determined according to its importance in the application of Smart production systems in SMEs. The weight of all experts was considered here as 0.2. Table 3 is the aggregated matrix of experts' opinion, which was created by applying E.q (1).

Table 3
Aggregated matrix of pairwise comparisons.

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
R_1	(1.00,1.00)	(0.80,1.38)	(0.24,4.36)	(0.13,8.59)	(0.16,6.12)	(0.18,6.12)	(0.15,6.15)	(0.27,4.57)
R_2	(1.38,0.80)	(1.00,1.00)	(0.51,1.25)	(0.12,8.14)	(0.24,4.08)	(0.19,4.36)	(0.21,6.15)	(0.72,1.62)
R_3	(4.36,0.24)	(1.25,0.51)	(1.00,1.00)	(0.15,6.92)	(0.65,1.25)	(0.27,3.73)	(0.16,4.13)	(0.23,3.37)
R_4	(8.59,0.13)	(8.14,0.12)	(6.92,0.15)	(1.00,1.00)	(8.16,0.12)	(7.38,0.15)	(6.43,0.16)	(8.59,0.12)
R_5	(6.12,0.16)	(4.08,0.24)	(1.25,0.65)	(0.12,8.16)	(1.00,1.00)	(3.00,0.24)	(5.16,0.19)	(1.93,0.42)
R_6	(6.12,0.18)	(4.36,0.19)	(3.73,0.27)	(0.15,7.38)	(0.24,3.00)	(1.00,1.00)	(2.55,0.35)	(3.68,0.25)
R_7	(6.15,0.15)	(6.15,0.21)	(4.13,0.16)	(0.16,6.43)	(0.19,5.16)	(0.61,2.55)	(1.00,1.00)	(3.90,0.19)
R_8	(4.57,0.27)	(2.14,0.23)	(3.37,0.23)	(0.12,8.59)	(0.42,1.93)	(0.25,3.68)	(0.19,3.90)	(1.00,1.00)

Then, according to the aggregated matrix, first, the initial directional diagram is drawn, and then, using the condition that among these elements, elements with $\rho_{ij} \geq 1$ must be selected; The final directed diagram is prepared. Figure 2 shows the final directed matrix.

Based on the number of outputs of each index, digitalization and real-time data connection index "R_4" with 7 outputs, as the most important index and modularity index "R_1" with zero output, as the least important index. the order of importance of the criteria is as follows:

$D_1^{our} = 0, D_2^{our} = 1, D_3^{our} = 2, D_4^{our} = 7, D_5^{our} = 5, D_6^{our} = 5, D_7^{our} = 4, D_8^{our} = 3$

$$D_4^{our} > D_5^{our} \,\&\, D_6^{our} > D_7^{our} > D_8^{our} > D_3^{our} > D_2^{our} > D_1^{our}$$

$\tau_4 \geq \tau_5 \geq \tau_6 \geq \tau_7 \geq \tau_8 \geq \tau_3 \geq \tau_2 \geq \tau_1$

and $\upsilon_4 \leq \upsilon_5 \leq \upsilon_6 \leq \upsilon_7 \leq \upsilon_8 \leq \upsilon_3 \leq \upsilon_2 \leq \upsilon_1$

Subsequently, by modeling using Models 1 and 2 and implementing them in Lingo software, the optimal weights for the degrees of membership and non-membership were obtained. The results of the criteria weights are presented in Table 4.

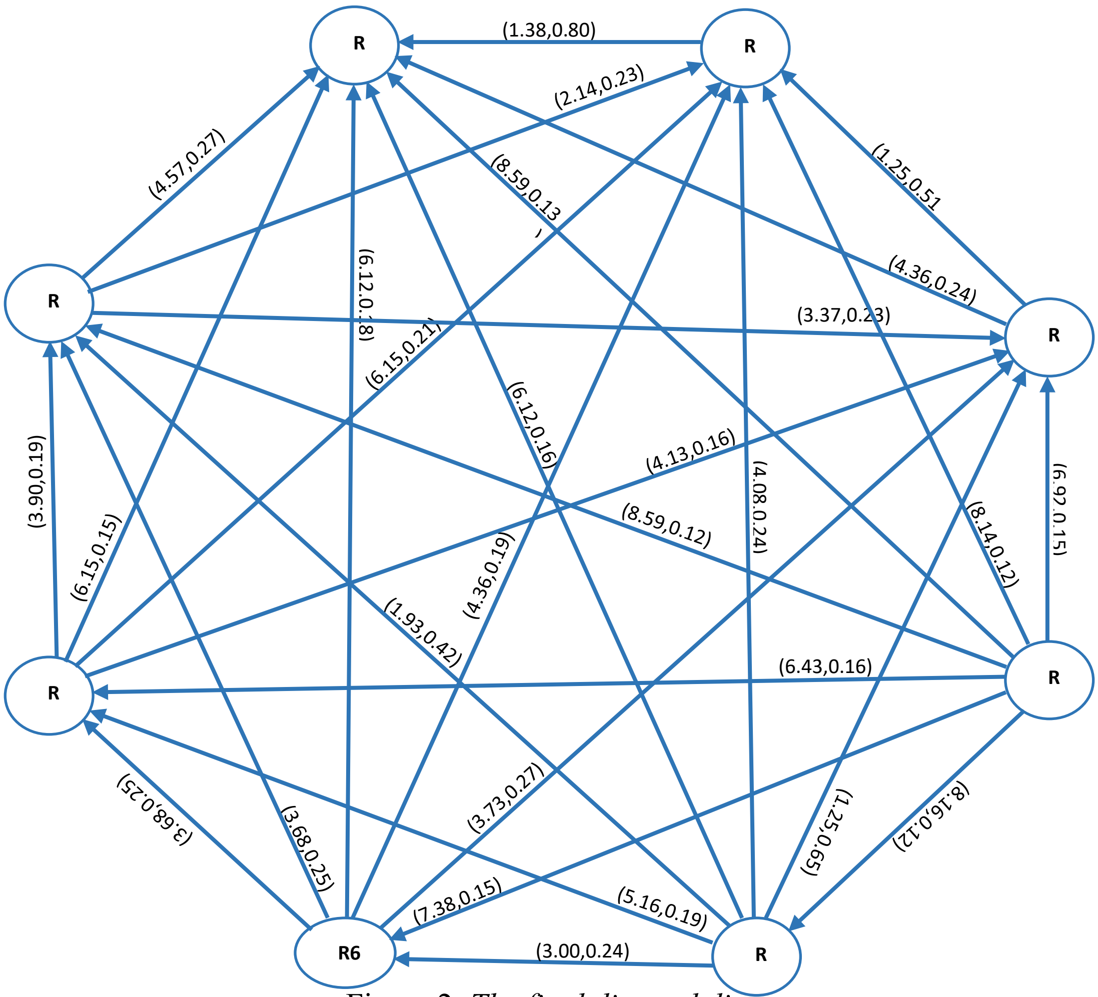

Figure 2. *The final directed diagram*

Table 4

The weights of the criteria using the IFMBWM

Requirements	Membership degree weight	rank	Non-Membership degree weight	rank
R_1	0.0417	8	0.2938	1
R_2	0.0860	7	0.2350	2
R_3	0.4125	6	0.1198	3
R_4	0.1361	1	0.0381	8
R_5	0.9674	2	0.0765	7
R_6	0.0960	3	0.0772	6
R_7	0.9207	4	0.0800	5
R_8	0.0204	5	0.0793	4

Using the E.q (3) indicators of incompatibility were determined.

$$CR = max\left\{\frac{\xi^*}{CI_1}, \frac{\zeta^*}{CI_2}\right\}=\left\{\frac{0.5742}{5.23}, \frac{0.00431}{0.08}\right\}= \{0.109\&0.00538\}=0.109$$

Given that the rate of intuitive fuzzy inconsistency is 0.109, and for a relationship to be consistent, the inconsistency rate must fall between 0 and 1, the paired comparisons are therefore consistent. As previously mentioned, after determining the weight of the factors, the TISM method was employed to understand the relationships between the requirements. The results of this analysis are presented below. On the basis, the knowledge base was created based on expert interpretations of these relationships, as shown in Table 5.

Table 5.
Knowledge base developed using expert's opinion

No	Factor	Paired comparison of factors	Interpretation of relationships
1	R_1-R_2	Modularity and agility interact with each other	Considering characteristics such as reconfiguration and flexibility to changes, which are both important aspects of agility and modularity, it can be said that these two requirements are effective in improving and upgrading each other.
2	R_1-R_3	Modularity affects flexibilit	Modularity can help the flexibility of the system by helping flexibility in different aspects.
3	R_1-R_4	Digitization and connection of real-time data has an effect on modularity	Digitization can improve the level of modularity by helping to improve the flow of information between all units of the system.
4	R_1-R_6	The Smartening of communication with stakeholders has an impact on modularity	Since the employees are the beneficiaries of the company, the **Smartening** of communication with these people can be effective in employing multi-skilled workforce and promote modularity.
5	R_1-R_7	Automation affects modularity	Automation can increase the level of modularity by helping to move tools and equipment automatically
6	R_2-R_3	Agility and flexibility have mutual influence on each other	Using processes and systems with higher flexibility helps to make production more agile.
7	R_2-R_4	Digitization and connection of real-time data has an impact on agility	Digitization and connection of real-time data can have a significant impact on agility by digitizing product development, improvement and management, as well as real-time product change needs assessment.
8	R_2-R_5	Robotization has an effect on agility	Robotization of various aspects of the production system can help to respond faster and thus become agile.
9	R_2-R_6	Smartening the relationship with stakeholders has an impact on agility	Smartening the relationship with the stakeholders by creating a better relationship with the customers and the supply chain can improve the agility of the system.
10	R_2-R_7	Automation affects agility	Automating various aspects of the production system can help to respond faster and thus become agile.
11	R_2-R_8	Smartening maintenance and inspection has an impact on agility	Repairs, maintenance and inspection are important things that contribute to the agility of the production system, which can be improved by making it smarter.
12	R_3-R_4	Digitization and connection of real-time data has an effect on flexibility	Cloud, machine learning, artificial intelligence, digital assistants and online robots, which are characteristics of digitization and real-time data connection, have a significant impact on the flexibility of the system.
13	R_3-R_5	Robotization affects flexibility	Robots of any kind; Online or physically, they seriously increase the flexibility of any process or system.
14	R_3-R_6	Smartening the relationship with stakeholders has an effect on flexibility.	Due to Smart communication with customers who are the main beneficiaries of any organization, the flexibility of the system increases to respond faster to the changing needs of customers.

No	Factor	Paired comparison of factors	Interpretation of relationships
15	R_3-R_7	Automation affects flexibility	It is obvious that automation will help the flexibility of tracking any system.
16	R_4-R_5	Digitization and connection of real-time data has an effect on Robotization	Online and web-based robots, as well as robots that have artificial and digital intelligence infrastructure, contribute significantly to the robotization of the system.
17	R_4-R_6	Digitization and connection of real-time data has an effect on the Smartening of communication with stakeholders.	Digitalization from various aspects such as decentralization (decentralization is the ability of Smart production systems to be managed by other subordinates) can increase the Smartening of communication with stakeholders. And in general, this intelligence will be created with the infrastructure of information technology.
18	R_4-R_7	Digitization and connection of real-time data has an effect on automation	Information and digital technology can significantly affect and improve automation from various spectrums in the concept of "fully automated factory".
19	R_4-R_8	Digitization and connection of real-time data has an effect on the Smartening of repairs and maintenance and inspection.	Digital technology can increase the smartness of maintenance with the help of quick diagnosis, and in general, this intelligence will be created with the infrastructure of information technology.
20	R_5-R_6	Robotization has an effect on the Smartening of communication with stakeholders.	Robotization , especially robots based on artificial intelligence, can improve this criterion with the rapid flow of information between different stakeholders.
21	R_5-R_7	Robotization has an effect on automation.	It is obvious that rationalization increases the level of automation.
22	R_5-R_8	Robotization has an effect on the Smartening of repairs and maintenance and inspection.	By using self-repairing robotic systems, the smartness of the repair and maintenance system increases.
23	R_7-R_8	Automation affects the smartness of maintenance and inspection	Automatic maintenance can increase the smartness of maintenance.

The final reachability matrix was obtained after creating the self-interaction matrix and also forming the initial reachability matrix, which is presented in Table 6.

Table 6.
The final reachability matrix

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	driving
R_1	-	1	1	0	0	0	0	0	2
R_2	1	-	1	0	0	0	0	0	2
R_3	1	1	-	0	0	0	0	0	2
R_4	1	1	1	-	1	1	1	1	7
R_5	1	1	1	0	-	1	1	1	6
R_6	1	1	1	0	0	-	0	0	3
R_7	1	1	1	0	0	0	-	1	4
R_8	1	1	1	0	0	0	0	-	3
dependency	7	7	7	0	1	2	2	3	-

By using the final reachability matrix of TISM process, the factors were classified using MICMAC analysis as shown in Figure 3.

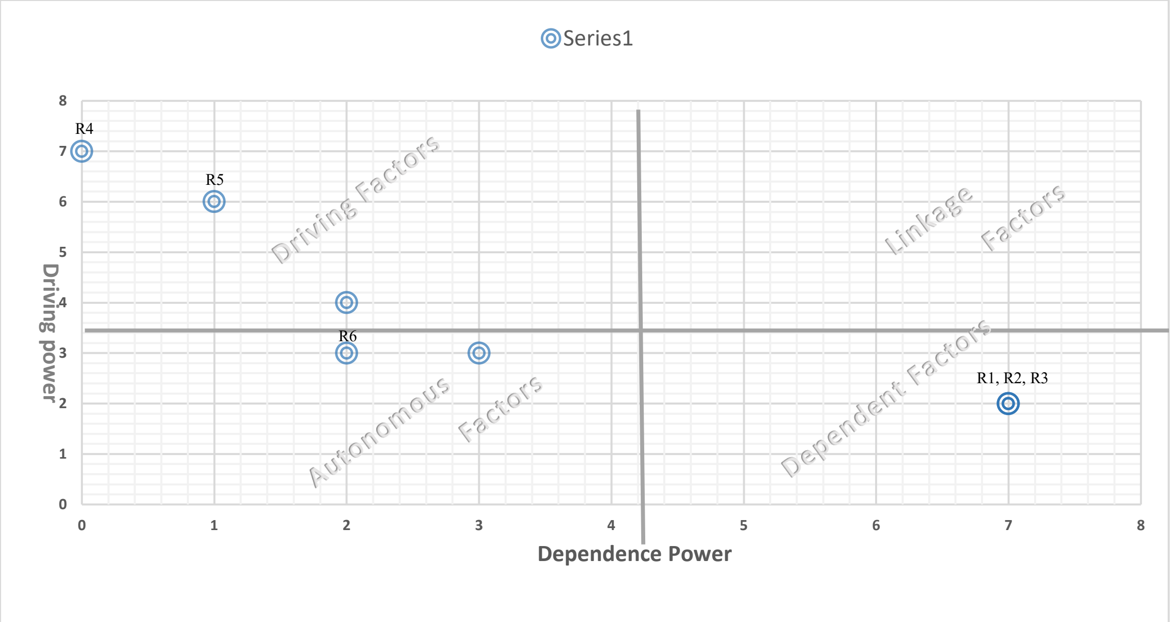

Figure 3. *MICMAC analysis of constituent factors (R_1-modularity, R_2-agility, R_3-flexibility, R_4-digitalization and real-time data connection, R_5-roboticization, R_6- Smartening of communication with stakeholders, R_7-automation, R_8- Smartening of repairs and maintenance and inspection)*

The hierarchical structure developed using TISM is shown in Figure 4 below, which depicts different dimensions with their contextual relationships as well as their relative importance based on the level they occupy in the diagram.

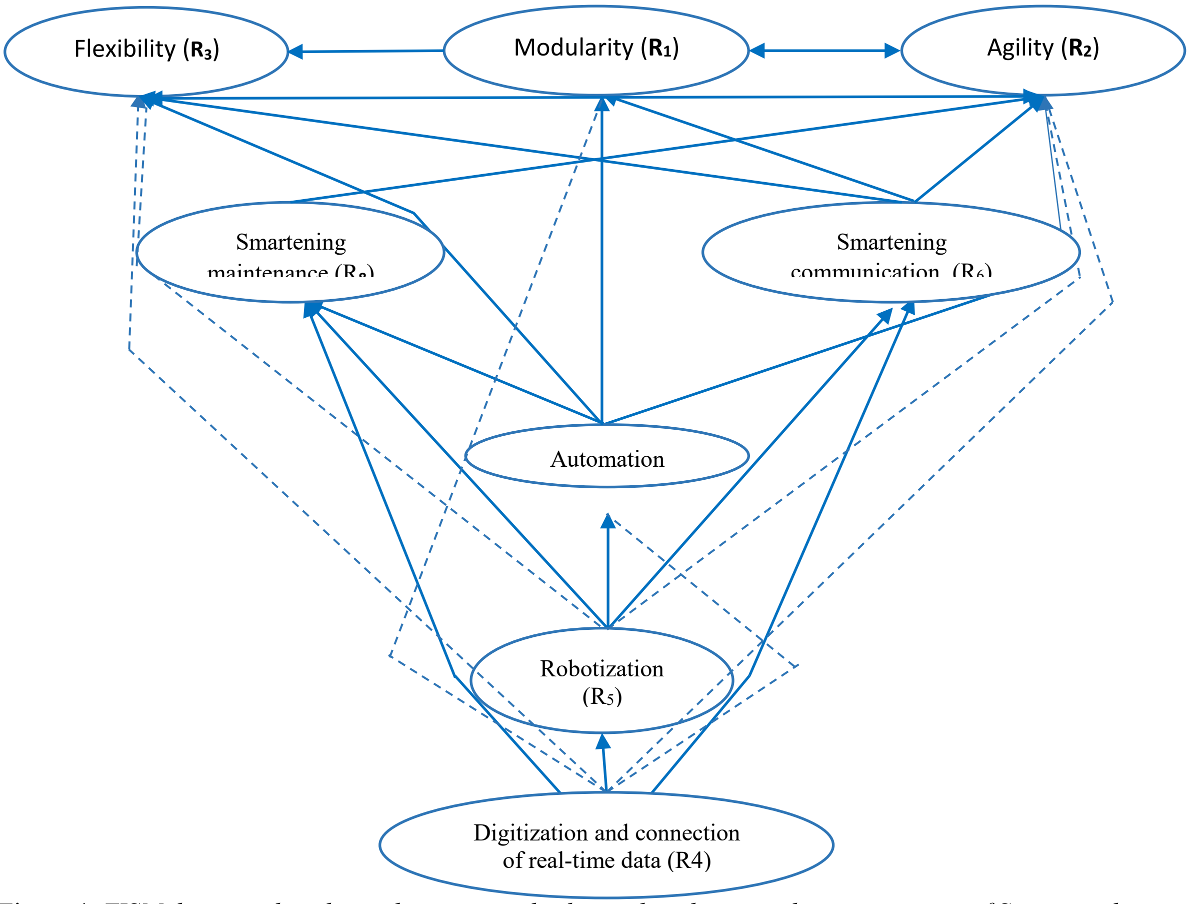

Figure 4. *TISM diagram that shows the contextual relationships between the requirements of Smart production systems*

Finally, a summary of the results of the two techniques used is given in Table 7, which compares the IFMBWM and TISM results. As can be seen, the only difference in the results; It is about R_5 and R_6 requirements. In the IFMBWM method, the higher rank belongs to R_6, and in the TISM method, the more basic level and, as a result, the better rank belongs to R_5.

Table 7

Comparing the results of quantitative and qualitative techniques

No.	Requirements	Method 1 IFMBWM Weight	IFMBWM Rank	Method 2 TISM level	TISM Rank	Variable type
R_1	Modularity	0.0417	8	1	5	Dependent
R_2	Agility	0.0860	7	1	5	Dependent
R_3	flexibility	0.4125	6	1	5	Dependent
R_4	Digitization and connection of real-time data	0.1361	1	5	1	Driving
R_5	Robotization	0.9674	2	4	2	Driving
R_6	Smartening communication with stakeholders	0.0960	3	2	4	Autonomous
R_7	Automation	0.9207	4	3	3	Driving
R_8	Smartening maintenance and inspection	0.0204	5	2	4	Autonomous

Discussion

Smart manufacturing systems are a fundamental concept for delivering contemporary services in a smartness manner. The implementation of these systems can be influenced by evolving social or industrial needs, global economic changes, and technological advancements. This necessitates the integration of innovative technologies to enhance and upgrade production systems, as well as to develop new systems aligned with smart production principles (Haricha et al., 2023). This study aimed to identify the factors that are critically important in the creation of smart production systems and to examine their relative importance and interrelationships for SMEs.

As observed, digitalization and real-time data connectivity, followed by robotics, were identified as the primary and most influential factors in this field, aligning with the existing literature. Most of the reviewed articles investigated the requirements, prerequisites, and characteristics of smart production through a systematic review method, with digitization and information technology being considered the main factors (Rauch and Vickery., 2020; Sharma and Villányi., 2022; Hammad et al., 2023; Haricha et al., 2023; Kılıç & Erkayman, 2023). The ICT, especially in certain industry sectors, provides powerful and compacted information in the service industry for organizations. It is very important to consider the widespread use of ICT for economic activities. First, the ICT directly leads to increased productivity and elevated economic growth of organizations. Secondly, it results in production and innovation, and the improvement of productivity and an important factor in advancing competitive advantage. Given the widespread use of information technology in business activities, governments are often portrayed in adaptation to the management practices experienced in the commercial world. The IT will play a dominant role in the new millennium, due to its very important capabilities, in improving the efficiency and effectiveness of the organizations' functional areas (Weber and Zink, (2014); Ghahremani & Saleh Ardestani, (2019)). In the limited number of articles that addressed this issue quantitatively (Qu et all., 2019; Qu et al., 2023; Malaga and Vinodh, 2023), this criterion, along with robotics and sometimes the combination of robotics with automation, was assigned the most weight and the most fundamental level. Some articles also paid special attention to agility criteria (Rauch and Vickery, 2019).

In general, most traditional factories possess operational technology resources that are not always interconnected. The current trend in smart production fundamentally relies on the increased use of information technology to save time, reduce costs, and enhance maintenance and services. This is achieved through the convergence of emerging technologies and platforms such as artificial intelligence and the Internet of Things, which represent innovative concepts in smart production (Mohammadi and Minaei, 2019). Digitalization aids in improving production forecasts, production planning, raw material inventory management, and overall factory resource management, thereby reducing waste and enhancing productivity. Small and medium-sized enterprises should focus on the vertical integration of data, from sales data in the enterprise resource planning system to production planning and control tools, down to machine data at the production unit level. Such integration is essential to leverage the connectivity of machines and workstations and to collect their data in real time. By installing IoT connectors and sensors, the challenge of transforming old machines into "Industry 4.0" machines can be addressed (Rauch et al 2019). In general, the concept of IoT is the connection of different devices to each other through the Internet. With the help of the Internet of Things, various programs and devices can interact with each other and even humans through an Internet connection. In fact, the Internet of Things enables people to manage and control the objects they use remotely with the help of Internet infrastructure (Babaie et a., 2022). The digitized work environment facilitates appropriate work studies and employee participation, enabling the factory to retain only skilled workers and, when necessary, to engage casual employees, thus reducing waste in terms of human resources. Consequently, accessing data in real time through the Internet of Things allows part of the team to be freed from certain tasks, enabling them to focus on more critical activities.

As noted by researchers such as Sharma and Villányi (2022), the necessity for businesses to restructure their entire organization into a digital entity has reached a peak. Businesses are increasingly recognizing the need for cloud technology and software as a service (SaaS) to efficiently manage their operations, from fulfilling digital and physical orders to ensuring employee comfort. Consequently, manufacturers are adopting cloud computing at an unprecedented rate. Conversely, with the advent of new emerging technologies in the market, such as high-speed and high-precision machines for milling and turning, as well as the introduction of cooperative robots, SMEs can advance further towards automation, even for small-scale production. When introducing new technologies in SMEs, it is essential that learning them is straightforward and cost-effective. For instance, the use of robots in SMEs is often hindered by the lack of experienced staff capable of programming robotic systems. One of the challenges of smart production systems for SMEs is their reliance on highly skilled personnel to program robotic devices, a resource that is often scarce in these companies. Therefore, robotic systems in smart production, like most cooperative robots in the market, should be user-friendly, easy to program, and simple to control (Sharma and Villányi, 2022)

In general, spending time on irrelevant tasks is detrimental to the organization. Automation and robotics enhance the efficiency and motivation of the production team by eliminating repetitive and monotonous tasks. Additionally, these two requirements ensure stable and uninterrupted production by reducing unplanned downtime due to equipment failure.

Managerial Implications

Managers and owners of SMEs can develop their production systems by considering these factors to create more durable systems and avoid incurring additional costs during the initial establishment phase. These factors have been identified from globally utilized literature and have been validated and localized by academic experts.

Based on the identified requirements and according to the research results of Rauch et al (2019), recommendations for organizational actions, particularly for managers, are proposed from short-term, medium-term, and long-term perspectives. In the short term, before establishing and developing their production systems, SMEs should aim to promote digitalization within daily organizational practices, beginning with simple activities such as paperless automation. This can be achieved using cost-effective digital tools and devices such as smartphones and tablets. In the medium term, it is crucial to introduce connectivity within the production unit. This entails implementing a comprehensive enterprise resource planning (ERP) system. Machines and workstations can be integrated with an ERP system or a manufacturing execution system (MES) to facilitate real-time exchange of production data. Additionally, SMEs should prioritize advanced production technologies. Technologies such as high-speed and high-precision Computer Numerical Control (CNC) machines, collaborative robots, and 3D printers are currently more economically viable for SMEs.

In the long term, smaller companies should gradually engage with topics such as artificial intelligence (AI) and machine learning. Although the widespread adoption of these technologies is expected in the coming years, early adopters will gain a competitive advantage in the market. Industrial designers of production systems, who are involved in creating processes and production systems within companies, can also utilize the findings of this study to develop and enhance their designs towards smart manufacturing and Industry 4.0.

Conclusion

This study provides a summary of the results and related observations, addressing the research questions outlined in the Introduction section. The requirements essential for establishing smart production systems are identified in eight categories, each serving as the foundation for a group of effective sub-criteria in smart production. These categories include modularity (R_1), agility (R_2), flexibility (R_3), digitalization and real-time data connectivity (R_4), robotization (R_5), smart communication with stakeholders (R_6), automation (R_7), and smart maintenance, repair, and inspection (R_8). These primary factors were identified through a review of the research literature and confirmed by consulting academic experts.

Subsequently, a multi-method approach was employed, utilizing the IFMBWM and the Total Interpretive Structural Modeling-MICMAC (TISM-MICMAC) qualitative technique to examine the relative importance of these factors in establishing smart production systems. Additionally, the interactions among these factors were investigated within the context of smart production. These factors were classified as independent, stimulating, and dependent variables, and their relative importance for the transition of small and medium-sized enterprises towards smart production was determined using the best-worst technique. The research findings indicated that:

1. Digitalization and real-time data connectivity are key requirements and powerful drivers in the creation of smart production systems.
2. Robotics, even on a small scale, can serve as a significant driving force in establishing these systems for small and medium-sized enterprises.
3. Enhancing communication with stakeholders can facilitate the acceptance of change among stakeholders, aiding small

and medium-sized enterprises in their transition towards smart production.

In this study, as with most applied research, there is a limitation regarding the generalizability of the relative importance of the requirements to other geographical regions, particularly developed countries, due to the fact that all experts consulted were from Iran. Additionally, despite employing the best-worst technique within an intuitive fuzzy environment, which significantly mitigates uncertainty in decision-making, the experts' opinions remain subjective and are influenced by the context and geographical scope of the study. Future researchers are encouraged to investigate sub-criteria for these main criteria. They may also explore topics such as sustainability and key issues in Industry 5.0 that could impact the development and success of smart manufacturing systems. Further research utilizing specific surveys and statistical generalization to a broader population can enhance the validity and reliability of the findings presented in this study.

Declaration of interest

The authors have no relevant financial or non-financial interests to disclose.

The authors have no competing interests to declare that are relevant to the content of this article.

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